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Social Attitudes: Investigations with Agent Simulations Using Webots

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Abstract

This article presents a multiagent simulation environment for studying agents' socio-political attitudes. It departs from a previously proposed concept of agents with socio-political attitudes, a high-level theoretical and conceptual model proposed by Petric et al. (2002) that was intended for conversational agents. In contrast, our work pursues a bottom-up simulation philosophy where attitudes are grounded in sensory-motor behaviour of spatially distributed autonomous agents, modelled in Webots simulation software. The original model was extended by defining an agent's socio-political type by means of weighting the three components found in the Petric et al. (2002) model (neo-liberal, alternative and fundamentalist), thus allowing the creation of mixed socio-political types. Also, in the simulations performed, issues were modelled as agents with variable levels of importance. Moreover, we introduced inter-agent communication capable of causing changes in socio-political types. Results are presented and discussed with respect to the initial research questions. According to our experimental results the following parameters did not have any significant impact on the simulation outcomes: initial physical position and orientation of the agents, positions of the issues, the issues' dynamics, and inter-agent communication. Experiments with different initial agent types showed that agents with indeterminate socio-political types tended to change to neo-liberal, alternative or fundamentalist agents. We conclude by proposing future extensions of the model. Our work is related to a trend in the Artificial Intelligence community which is not primarily task or problem-solving oriented, but rather focuses on the study of the embodied and situated nature of social behaviour in humans.

Keywords:

Agent Simulation; Social Attitudes; Social Behaviour; Social Simulation; Socio-political Attitudes; Webots

Introduction and Background

1.1

The starting point for the research described in this paper was a concept of agents with socio-political attitudes, inspired by a high-level theoretical and conceptual model proposed by Petric et al. (2002) for the development of a social attitude engine for believable conversational agents. In their work, the authors proposed that the social attitude engines and emotion engines of autonomous agents should be separated. Further, as a base of a new *social engine* they suggest a conceptual model of agent *socio-political attitudes*, presented in the form of a table (Table 1). Petric et al. (2002) are starting from Jean-Francois Lyotard's notion of 'metanarratives'[1]. Agent attitudes were derived from their grand narratives or their ideologies. Three globally recognizable ideal types (neo-liberal, fundamentalist, and alternative) were supplied with narratives that were translated into a form suitable for modelling (Table 1).

Issue	Neo-liberal	Alternative	Fundament
Market	+	0	-
Individualism	+	0	-
Flexibility	+	0	-
Tradition	-	0	+
War	0	-	+
Religious tolerance	0	+	-
Materialism	+	0	-
Redistribution of wealth	-	+	0

Table 1. Socio-political attitudes, of three ideal types, toward issues that are selected from their stories (grand narratives), as presented in Petric et al. (2002)

1.2

In Table 1, which represents their proposed conceptual model, Petric et al. (2002) reduced the agent's social attitudes to simple oppositions (+, -) or absence of attitude (0). The table is a simplification of a more complex table with statements and issues derived from agents' metanarratives and based on the model of 'ideal type'. The plus sign indicates a positive attitude, a minus sign a negative attitude, and a zero sign indicates a neutral attitude towards an issue.

1.3

Petric et al. (2002) suggested this conceptual model as a basis for the development of a social attitude engine for believable conversational agents. They proposed that a set of statements with detailed expressions of the basic attitudes should be added to every cell in the table (i.e. to every plus, minus or zero sign). According to Petric et al. (2002), the interaction of agents developed from this model, should provide an environment suitable for studying human social behaviour.

1.4

The model described above was the starting point for the development of our model. Contrary to the high-level theoretical and conceptual model, meant for the development of social attitude engine for believable conversational agents, the simulation and the underlying model that we developed is based on a bottom-up simulation perspective. In our model, both agents and issues are modelled as spatially distributed agents in a virtual Webots simulation world where attitudes emerge from sensory-motor behaviour and interactions among the agents and issues. The focus of our research interest is the dynamics of agents' attitude change in relation to the agents' interactions. In our virtual environment the convergence of agents' attitudes towards issues is modelled using a spatial metaphor, namely using an agent's spatial (Euclidean) distance to an issue as an indicator of the agent's strength of attitude towards that issue.

Related Work

2.1

Social attitudes and social behaviour are widely discussed topics in the autonomous software agents and simulation community.

2.2

In the context of Distributed Artificial Intelligence, agent social behaviour is a dominant factor in agents' coordination in goal attainment and task completion (Weiss 1999), negotiation and cooperation in order to realize a goal (Wooldridge 1999), and in communication to achieve better goals for themselves and society (Huhns and Stephens 1999). Kalenka and Jennings (1995) also discuss social attitudes in the context of autonomous problem solving agents.

2.3

Other works that are closely related to the BDI agent architecture consider social attitudes in the context of agent cooperative activity (delegation and adoption), closely related to the term 'personality traits' (Castelfranchi et al. 1997). However, some critics of this architecture stress its deficiencies in social behaviour simulation (Guye-Vuillème and Thalmann 2001; Balzer 1997).

2.4

Researchers, in the field of believable agents, often discuss social attitudes in the context of a socio-psychological model (Rousseau and Hayes-Roth 1998), or an emotional model (Reilly and Bates 1992), based on cognitive psychology approaches. Sengers (2000) discusses the 'aliveness' of most AI agents optimised for formal intelligence or for use as a goal orientated tool. Dautenhahn et al. (2002) criticises the social believability of existing multi-agent systems that are "often only loosely related to human social intelligence, or use very different models from the animal world, e.g. self -organisation in social insects societies, or might strongly focus on the engineering and optimisation aspects of the agent approach to software engineering". In addition, Rouchier (2002), in her review of some Multi Agent Systems (MAS) principles, stressed some shortcomings of existing ideas for achieving social intelligence.

2.5

In the field of social simulation, we find algorithmic approaches that address social attitudes, but most are not agent-based. Social attitudes are often mentioned only in the context of social networks (Stocker et al. 2002), or inter-group relations (Suleiman and Fischer 2000).

2.6

The Webots simulation software was used in order to perform a social simulation. Webots is a simulation software package widely used in autonomous agents and robotics research. The agents typically modelled in Webots have a robotic shape and an associated behaviour repertoire. Webots provides a library of such agents, including the *Khepera* which faithfully models the widely used mobile robot with the same name. The investigation of social behaviour in Webots simulations to date has been mainly concerned with the behaviour of social insects (Newton 2002; Ijspeert et al. 2001), other Artificial Life experiments, or testing action-selection architectures (Avila-García and Cañamero 2002). Rarely has this simulator been used for modelling aspects characteristic of human-like agents, cf. (Dautenhahn and Coles 2001). [2]

2.7

In contrast to previous research, cited above, our work is related to a trend in the Artificial Intelligence community, which is not primarily task or problem-solving oriented, but rather focuses on the study of the embodied and situated nature of social behaviour in humans. In our simulation model, which is inspired by the high-level theoretical and conceptual model, agent behaviour is strictly related to the agents' embodied behaviour in the simulated environment. Social attitudes are directly represented as behaviour in the environment.

Model

3.1

The model presented here departs from the conceptual model proposed by Petric et al. (2002). In our model, the ideologies i.e. neo-liberal (n), alternative (a) and fundamentalist (f), are enhanced by providing a weighting for each of the three components.

Agents

3.2

Each agent's socio-political type component (neo-liberal, alternative and fundamentalist) has three possible values: 0, 0.5 or 1. In Figure 1, three examples of agents and their socio-political types are shown.

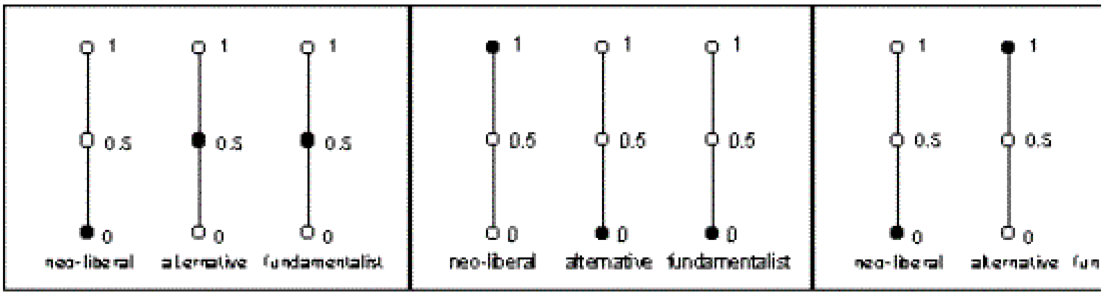


Figure 1. Examples of three different agents: agent with indeterminate socio-political type (neo-liberal component is 0, alternative component is 0.5 and fundamentalist component is 0.5), neo-liberal agent (n=1, a=0, f=0) and alternative agent (n=0, a=1,

f=0)

3.3

For the sake of simplicity, there is a limited number of possible agent socio-political types in this simulation. The socio-political type components (n), (a) and (f) must sum to 1 for every agent (n+a+f=1). Figure 2 therefore represents all possible agent types in this simulation. Next to neo-liberal, alternative and fundamentalist socio-political types, there are three other indeterminate agent types.

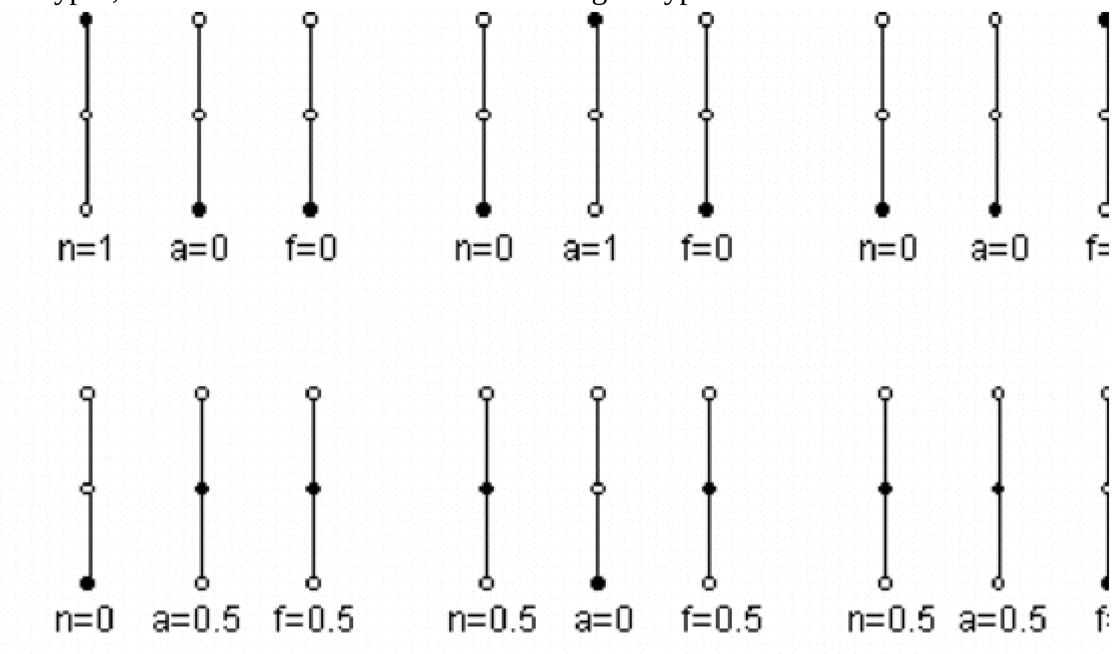


Figure 2. All possible agents' socio-political types that could occur in the simulation. Top: neo-liberal, alternative and fundamentalist agent. Bottom: agents with indeterminate socio-political type

3.4

Issues, toward which agents have attitudes, were adapted from Petric et al. ([2002](#)). Attitudes toward issues are calculated according to Table 2. The AGENT column consists of all six agent types. The ISSUE column comprises the attitude values from Table 1. Attitude signs from the original table are now converted in -1, 0 and 1 values. For each issue the ATTITUDE column calculates the attitude values based on the fore-mentioned two columns.

AGENT			ISSUE			ATTITUDE	ISSUE			ATTITUDE	ISSUE			ATTITUDE	ISSUE		
			market			mar	individualism			ind	flexibility			flx	tradition		
n	a	f	+	0	-		+	0	-		+	0	-		-	0	+
1	0	0	1	0	-1	1	1	0	-1	1	1	0	-1	1	-1	0	1
0	1	0	1	0	-1	0	1	0	-1	0	1	0	-1	0	-1	0	1
0	0	1	1	0	-1	-1	1	0	-1	-1	1	0	-1	-1	-1	0	1
0	0.5	0.5	1	0	-1	-0.5	1	0	-1	-0.5	1	0	-1	-0.5	-1	0	1
0.5	0	0.5	1	0	-1	0	1	0	-1	0	1	0	-1	0	-1	0	1
0.5	0.5	0	1	0	-1	0.5	1	0	-1	0.5	1	0	-1	0.5	-1	0	1

AGENT			ISSUE			ATTITUDE	ISSUE			ATTITUDE	ISSUE			ATTITUDE	ISSUE		
			war			war	relig. toler.			rel	materialism			mat	redistribution		
n	a	f	0	-	+		0	+	-		+	0	-		-	+	0
1	0	0	0	-1	1	0	0	1	-1	0	1	0	-1	1	-1	1	0
0	1	0	0	-1	1	-1	0	1	-1	1	1	0	-1	0	-1	1	0
0	0	1	0	-1	1	1	0	1	-1	-1	1	0	-1	-1	-1	1	0
0	0.5	0.5	0	-1	1	0	0	1	-1	0	1	0	-1	-0.5	-1	1	0
0.5	0	0.5	0	-1	1	0.5	0	1	-1	-0.5	1	0	-1	0	-1	1	0
0.5	0.5	0	0	-1	1	-0.5	0	1	-1	0.5	1	0	-1	0.5	-1	1	0

Table 2. The calculations of an agent's attitudes toward each issue according to the agent's socio-political type

3.5

As may be seen from the table above, an agent may possess five possible attitude values (Table 3), comprising two negative (-1 and -0.5), two positive (0.5, 1), and neutral (0). These attitudes could be viewed as corresponding to the Likert attitude scale (Likert 1932) with an additional neutral (middle) value.

Table 3: All possible agent attitudes

attitude value	attitude
1	very positive
0.5	positive
0	neutral
-0.5	negative
-1	very negative

Issues

3.6

As was mentioned before, the issues, towards which agents have attitudes, were adapted from Petric et al. (2002). However, in our simulations, every issue has dynamically changing features. To this purpose, we implemented for each issue a so-called 'level of importance'. An issue with a high number of agents around it becomes more 'important' in the simulation world. This parameter is set to 'normal' at the start of a simulation, but changes to 'high' every time a high number of agents are present in the physical space around that issue. A high level of importance for each issue is manifested in a higher agent attitude toward that issue. For instance, if an agent's attitude toward an issue with a normal level of importance was originally 0, then, for the same issue with a high level of importance, the attitude will be 0.5. If the number of agents around an issue decreases, then the issue's level of importance returns to normal. There is no option for decreasing the issue's importance level below normal. All possible transitions are presented in Table 4.

Table 4: Changes in an agent's attitude toward issues dependent on the issue's level of importance

level of importance	
normal	**high**
-1	-0.5
-0.5	0
0	0.5
0.5	1
1	1

Communication

3.7

Since humans change their attitudes not only in interaction with the issues, but also in communication with other agents, we decided to include inter-agent communication in our simulations. Agents communicate every time they are physically close within the environment. A communication algorithm defines how they may change their socio-political type. The model of communication that was chosen is presented in Table 5. The first two columns consist of all possible combinations of different agent types. The CALCULATION column represents the average values of both agents' socio-political types (each type with three components). The last two columns in the table show the resulting socio-political types of the two agents after communication.

BEFORE COMMUNICATION						CALCULATION			AFTER COMMUNICATIC				
AGENT 1			AGENT 2						AGENT 1			AGEN	
n	a	f	n	a	f	n	a	f	n	a	f	n	a
1	0	0	1	0	0	1	0	0	1	0	0	1	0
1	0	0	0	1	0	0.5	0.5	0	0.5	0.5	0	0.5	0.5
1	0	0	0	0	1	0.5	0	0.5	0.5	0	0.5	0.5	0
1	0	0	0	0.5	0.5	0.5	0.25	0.25	1	0	0	0	0.5
1	0	0	0.5	0	0.5	0.75	0	0.25	1	0	0	1	0
1	0	0	0.5	0.5	0	0.75	0.25	0	1	0	0	1	0
0	1	0	0	1	0	0	1	0	0	1	0	0	1
0	1	0	0	0	1	0	0.5	0.5	0	0.5	0.5	0	0.5
0	1	0	0	0.5	0.5	0	0.75	0.25	0	1	0	0	1
0	1	0	0.5	0	0.5	0.25	0.5	0.25	0	1	0	0.5	0
0	1	0	0.5	0.5	0	0.25	0.75	0	0	1	0	0	1
0	0	1	0	0	1	0	0	1	0	0	1	0	0
0	0	1	0	0.5	0.5	0	0.25	0.75	0	0	1	0	0
0	0	1	0.5	0	0.5	0.25	0	0.75	0	0	1	0	0
0	0	1	0.5	0.5	0	0.25	0.25	0.5	0	0	1	0.5	0.5
0	0.5	0.5	0	0.5	0.5	0	0.5	0.5	0	0.5	0.5	0	0.5
0	0.5	0.5	0.5	0	0.5	0.25	0.25	0.5	0	0.5	0.5	0.5	0
0	0.5	0.5	0.5	0.5	0	0.25	0.5	0.25	0	0.5	0.5	0.5	0.5
0.5	0	0.5	0.5	0	0.5	0.5	0	0.5	0.5	0	0.5	0.5	0
0.5	0	0.5	0.5	0.5	0	0.5	0.25	0.25	0.5	0	0.5	0.5	0.5
0.5	0.5	0	0.5	0.5	0	0.5	0.5	0	0.5	0.5	0	0.5	0.5

Table 5. All possible communication situations between two agents and resulting agent types

3.8

The possible results of the communication process are either: a common socio-political type for both agents based on their previous types, or unchanged types for both agents after communication. Some agents' communication examples are shown in Figure 3.

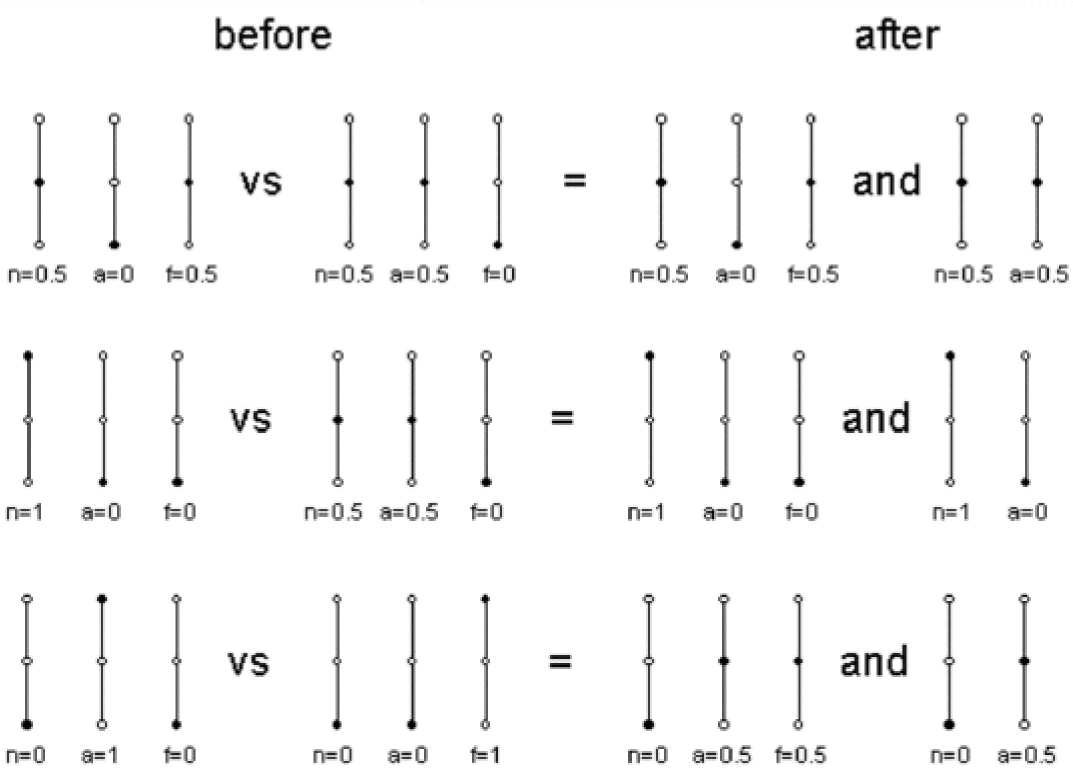


Figure 3. Three examples of the potential outcomes of inter-agent communication. Top: a communication where both agents retain their initial socio-political types. Middle: a neo-liberal agent influences the second agent and, as a result, the second agent changes its type to neo-liberal. Bottom: both agents' types have changed as a consequence of inter-agent communication

3.9

The simple communication algorithm that we used limits the number of different agent types after communication. It was chosen for the sake of simplicity and easier collection of simulation results. Discussions about the adequacy of the algorithm are given after the analysis of the simulation results.

Implementation

Webots

4.1

As previously mentioned, the simulation is implemented in Webots (www.cyberbotics.com). The Webots simulation software is designed to model the circumstances of real world robotic experiments as closely as possible. To model the real world conditions that would apply if real robots were used, Webots adds 10% of white noise to the sensor measurements of light and proximity. Because of random input, each simulation run is different, even when identical experimental parameters and initial conditions are set. The world (environment, agents, lights and objects) is described in VMRL (Virtual Reality Modelling Language). Control of the agents, through agent-specific nodes, is performed by controller software written in the C programming language.

4.2

In this work, our model is grounded into sensory-motor behaviour of spatially distributed autonomous agents. The ability to model a small number of embodied (at a very basic level) agents, with sensors and actuators, and to have this model relate closely to a real world scenario (a physical environment) was an important reason for choosing the Webots software. In our work, we selected Webots primarily because it provided a simulation environment for embodied agents, rather than using it to help with the preparation of robot experiments. Nevertheless, the same programmes that we developed to control the simulated agents could in principle also be transferred to physical robots.

4.3

The possible alternative choices of simulation environments, for example Swarm (www.swarm.org), are more orientated toward big multiagent simulations as opposed to embodiment, and were therefore less suitable in this context.

Agents

4.4

In accordance with the Webots design philosophy, the ready-made standard Khepera[3] robot was used for agents (Figure 4). The robot/agent is equipped with eight infrared type sensors. Only front and side sensors (six in total) were used (as shown in Figure 4). Every robot/agent is autonomous and controlled by a separate controller program. The robot is cylindrical and its height is relatively small.

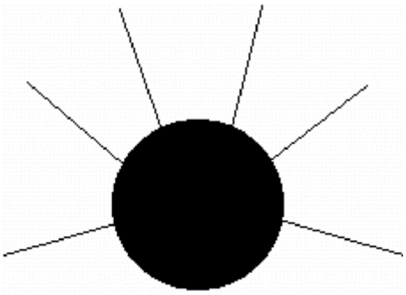


Figure 4. Khepera robot/agent and sensors used in the simulation (lines represent the range of sensors that measure distance to objects)

4.5

At the start of a simulation run, every agent has a characteristic socio-political type. As explained before, these types consist of three components: neo-liberal (n), alternative (a) and fundamentalist (f). According to the particular experimental situation to be simulated, a specific type could be defined at the start of a simulation run, or may be chosen randomly. When the agent starts moving randomly in the arena it senses the surrounding world by checking its sensors and receiver. As it approaches an issue object, its receiver detects the object's issue type. The agent then changes its behaviour in accordance with its attitude towards that issue. Next, a calculation is performed based on the agent type, the issue detected and using Table 2. The behaviour of an agent towards an issue is implemented in terms of the agent moves in the arena. Six types of agent behaviour are introduced: 'turn', 'slow turn', 'avoid', 'around', 'approach' and 'random'. These behaviours were selected in order to reflect the agent's attitude toward the encountered issue (Table 6).

Table 6: All possible agent behaviours in the simulation

Attitude	agent	description

	behaviour	
-1	turn	immediately turn around from issue
-0.5	slow turn	turn around from issue
0	avoid	avoid issue
0.5	around	stay around issue
1	approach	approach issue
NO ISSUE DETECTED	random	random moving

4.6

These behaviours are implemented in the agent's controller software based on a Braitenberg algorithm (Braitenberg 1984; Arkin 1998), using the various sensors and different robot motor speeds.

Issues

4.7

Each issue agent is represented as a physical spot in the simulation arena and attracts all agents that have a positive attitude toward that issue. Issues are modelled as custom robot VRML nodes, cylindrical in form, stationary and without wheels but with sensors and emitters that enable them to perceive and respond to the environment. Every issue agent has 12 infrared type sensors around its perimeter which are used for sensing the presence of agents around the issue (Figure 5). The emitter is used to transmit the issue's content as strings: 'mar'(market), 'ind'(individualism), 'flx'(flexibility), 'tra'(tradition), 'war'(war), 'rel'(religious tolerance), 'mat'(materialism) and 'red'(redistribution of wealth). Agents perceive these messages (strings), and can distinguish between different issues. The area of influence within which these messages can be detected by the agents has been adjusted following many test runs.[4]

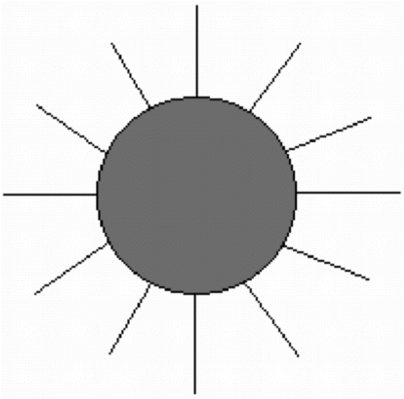


Figure 5. Issue robot/agent and sensors used for an issue agent (lines represent sensors and their range)

4.8

A controller program controls the issue's emitter. In passive issue mode, each issue constantly emits just one of these strings. In active issue mode, according to the number of active sensors (sensors that detect a robot/agent) in each simulation step, the emitted string may change between 'MAR', 'IND', 'FLX', 'TRA', 'WAR', 'REL', 'MAT', and 'RED'. Here the upper-case letters denote the higher importance of these issues for the agent (Table 7). In simulation test runs we determined that the best number of sensors, which need to be activated to raise an issue's importance to a higher level, is three. We chose this value following many test runs and found that in most cases it corresponded to the presence of three agents around an issue. The selection of this value exemplifies the importance of consequences of the (virtual) embodiment of our agents: two agents cannot occupy the same space in the world at the same time.[5]

Table 7: Strings emitted by an issue depending on its level of importance

issue	**emitted string**	
	normal level of importance	**high level of importance**
Market	'mar'	'MAR'
Individualism	'ind'	'IND'
Flexibility	'flx'	'FLX'
Tradition	'tra'	'TRA'
War	'war'	'WAR'
Religious tolerance	'rel'	'REL'
Materialism	'mat'	'MAT'
Redistribution of wealth	'red'	'RED'

Communication

4.9

Each robot/agent is also equipped with an emitter and another receiver. An agent constantly emits its socio-political type and its number in the form of a message. An example of such a message is '7550', which translates to "I am agent number 7 with n=0.5, a=0.5, f=0 type components". Inter-agent communication emitters and receivers operate on a different channel from the issues' emitters. The emission range, adjusted as a result of many simulation test runs, was slightly greater than that of the issues'. The agent's communication receiver constantly senses other agents' emissions. On receiving another agent's messages, it calculates its new state by reference to the communication (Table 5). The second agent involved in the communication also performs the same calculations.

World

4.10

There are nine agents in the simulation Webots world. This number was chosen in part because of limitations of the Webots software[6], but also because the model requires three distinct types of agents. Eight different issues and nine agents are distributed in the simulation arena. The arena takes the form of a rectangular area bounded by walls. An aerial view of the simulation world is shown (Figure 6) because our primary interest is to observe changes of movements in 2D. The agents, issues and the environment are in fact modelled in 3D.

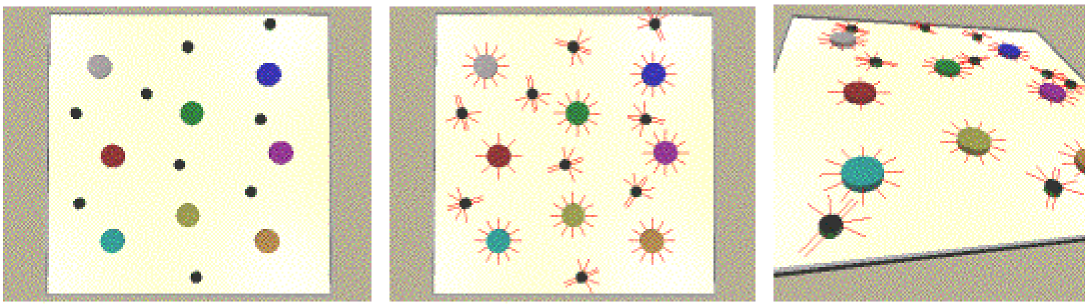


Figure 6. Simulation world in the initial configuration. There are nine agents (shown in black) in the arena, and eight issues, each with a different colour. Agents and issues' are randomly distributed. The diagram in the middle shows agents' and issues sensor ranges and positions. The right diagram shows a 3D view of the world

Supervisor

4.11

In our experiments a special Webots VRML node, called the supervisor, is used. It is an omniscient robot/agent that has information about the whole simulation world. Normal robots/agents in Webots only have a local view of the world. The supervisor can detect agents' positions and calculate their distances from the issues closest to them. In addition, the supervisor saves a picture of the world at the end of the simulation. The supervisor is a convenient means for monitoring and evaluating experiments in Webots, it is not used in our experiment for actually controlling or otherwise influencing the experiments and the agents, which only have a local perspective in the world.

Simulation

5.1

At the start of each simulation, the agents start to move randomly. They avoid obstacles (walls, issues and other agents), change their behaviour according to distance from issues, and communicate with each other. The simulation makes use of discrete simulation steps, each of 64ms duration. Every simulation run comprised of 1000 steps, which was judged a suitable length following many test runs. The following research questions were selected as the focus of our simulations.

a. How do the initial physical positions of agents and issues in the environment influence the simulations?
b. How do the issues' dynamics influence the simulation outcomes?
c. What is the impact of inter-agent communications on the simulation results?
d. How does the choice of the initial agent types change the simulation results?
e. How exactly do the agents change types during the simulation?

Experimental runs

5.2

In order to address the above-mentioned research questions, 80 different experimental situations were selected. They are summarised in Table 9.

5.3 The five situations selected for observing the influence and change of the initial agent types in the simulation are shown in rows numbers from 3 to 7. The first situation has random agent types (number 3) in the arena at the start. In the second case, there are three agents of neo-liberal, alternative and fundamentalist types (number 4). The third and fourth experimental set-ups contain one neo-liberal or alternative agent among eight other types of agent (numbers 5 and 6). The last situation has just one alternative agent among four neo-liberal and four fundamentalist agents (number 7).

5.4 For observing the influence of agents' and issues' initial positions on the simulation, every experimental situation with two different distributions of issues in the arena were run. Moreover, each of them was studied with two different agent distributions. Two types of initial distribution were selected, one more distributed and one more clustered (i.e. agents with the same type were positioned closely to one another in the arena). For each situation identified in Table 8, simulations were run five times. The agents' orientation at the start of the simulation was chosen randomly for every single simulation run.

5.5 All simulation runs were repeated for passive issues and active issues. All eight situations were then repeated with inter-agent communication. The influence of the issues' dynamics and inter-agent communications were recorded.

NO	AGENTS	COMMUNICATION OFF								COMMUNICATION ON							
		ISSUES PASSIVE				ISSUES ACTIVE				ISSUES PASSIVE				ISSUES ACTIVE			
		agents pos 1		agents pos 2		agents pos 1		agents pos 2		agents pos 1		agents pos 2		agents pos 1		agents pos	
		issues pos 1	issues pos 2	issues pos 1	issues pos 2	issues pos 1	issues pos 2	issues pos 1	issues pos 2	issues pos 1	issues pos 2	issues pos 1	issues pos 2	issues pos 1	issues pos 2	issues pos 1	issu pos
3	random	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5
4	3n/3a/3f	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5
5	8n 1a	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5
6	8a 1n	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5
7	4n 4f 1a	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5

TOTAL RUN

Table 8. Number of all different simulation runs (400) carried out in this work

NO	AGENTS	COMMUNICATION OFF								COMMUNICATION ON						
		ISSUES PASSIVE				ISSUES ACTIVE				ISSUES PASSIVE				ISSUES AC		
		agents pos 1		agents pos 2		agents pos 1		agents pos 2		agents pos 1		agents pos 2		agents pos 1		ag
		issues pos 1	issues pos 2	issues pos 1	issues pos 2	issues pos 1	issues pos 2	issues pos 1	issues pos 2	issues pos 1	issues pos 2	issues pos 1	issues pos 2	issues pos 1	issues pos 2	iss po
3	random	3p1	3p2	3p3	3p4	3a1	3a2	3a3	3a4	3cp1	3cp2	3cp3	3cp4	3ca1	3ca2	3c
4	3n/3a/3f	4p1	4p2	4p3	4p4	4a1	4a2	4a3	4a4	4cp1	4cp2	4cp3	4cp4	4ca1	4ca2	4c
5	8n 1a	5p1	5p2	5p3	5p4	5a1	5a2	5a3	5a4	5cp1	5cp2	5cp3	5cp4	5ca1	5ca2	5c
6	8a 1n	6p1	6p2	6p3	6p4	6a1	6a2	6a3	6a4	6cp1	6cp2	6cp3	6cp4	6ca1	6ca2	6c
7	4n 4f 1a	7p1	7p2	7p3	7p4	7a1	7a2	7a3	7a4	7cp1	7cp2	7cp3	7cp4	7ca1	7ca2	7c

Table 9. All different experimental situations (80) studied in this work

Data and evaluation criterion

5.6 For each simulation run from Table 8, the following data was collected:

- The sum of every agent's distance from its closest issue in every simulation step.
- The types of agents in the arena at the end of the simulation.

- The number of contacts between agents during simulation.
- A screenshot of the arena at the end of each simulation.

5.7 Examples of arena screenshots at the end of the simulation (after 1000 simulation steps) are shown below (Figure 7).

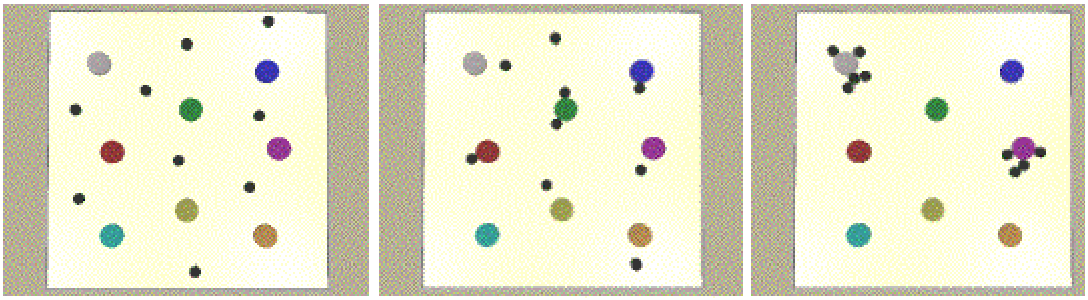


Figure 7. Left: screenshot of the simulation at the start. Middle and right: screenshots at the end of two different simulation runs

The sum of all agents' physical distances from their closest issue in the arena was measured for every simulation step. We calculated a value D as an indicator of the agents' spatial convergence towards the issues during the run. Its degree of fluctuation shows how smoothly the agents converge[7].

$$D = \sum_{i=1}^{N} d_i$$

D - Sum of all agents' distance from their closest issue.
d_i - Distance of agent number 'i' from its closest issue.
N - Number of agents (N=9).

5.8 For each experimental situation the average convergence graph of D and the joined standard error graph for 1000 simulation steps were computed. The standard error graphs comprise the average values and standard error values (Snedecor and Cochran 1980) for every simulation step (average D + SE and average D - SE). The standard error graphs are an indication of the stability of D during simulation.

5.9 The evaluation criteria for every experimental situation were the convergence value D, the standard error of D, and the number of different agent types in the arena.

Reference experiments

5.10 After test experimental runs, a set of reference simulations were run. The reliability of the simulation environment and the results of the simulation and evaluation criteria was tested in 60 reference runs. Three different experimental situations were chosen. The convergence D graph, the standard error of D graph, and the simulation screenshots were analysed for every reference situation.

5.11 The reference runs determined that our simulation is running as expected and that there are no unexpected irregularities, deadlocks or visible bugs in the Webots software. It also confirmed that the convergence value D and the standard error of D are reliable indicators of the prevailing situation in the arena during simulation.

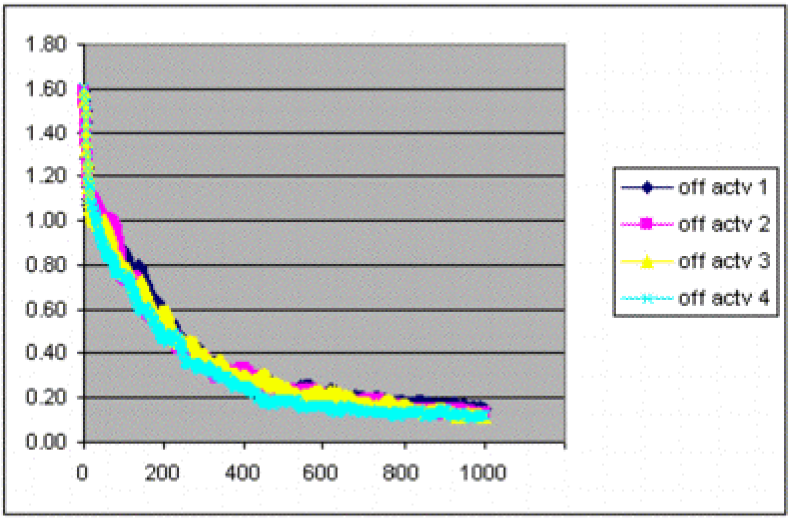
6 Results and Discussion

6.1

For every different experimental situation (every cell entry in Table 9), the convergence D graph and standard error graph were computed. The number of different agent types in the arena was collected, and arena screenshot at the end of simulation was taken. All the data were analysed and a summary of all results is presented below.

The influence of agents and issues initial physical positions on the simulation

Every experimental situation was run for two different positions of agents and issues in the arena (distributed and clustered). In Figure 8 and 9, the convergence D for each of these four positions are presented. Each graph line presents 25 different experiment runs (5 runs for 5 experimental situations from Table 8).



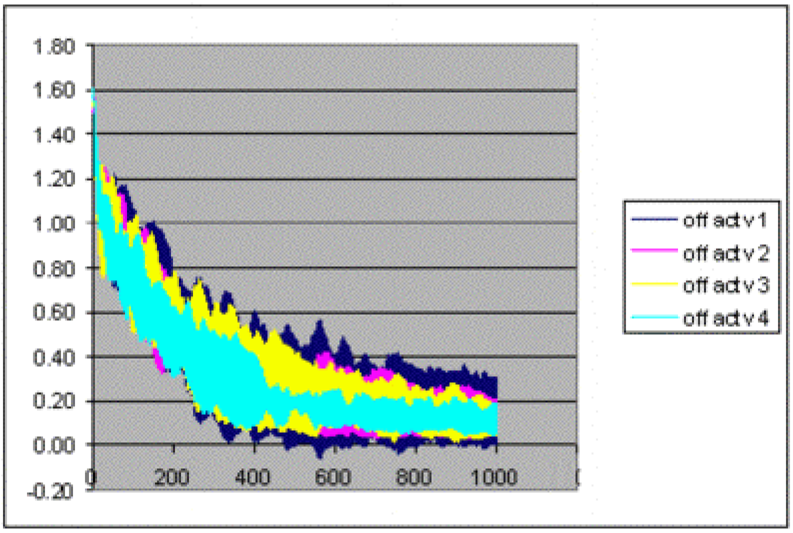


Figure 8. Convergence value D for two different agent positions with two different issue positions (communication off, active issues). Average value graph (left) and standard error graph (right) are shown

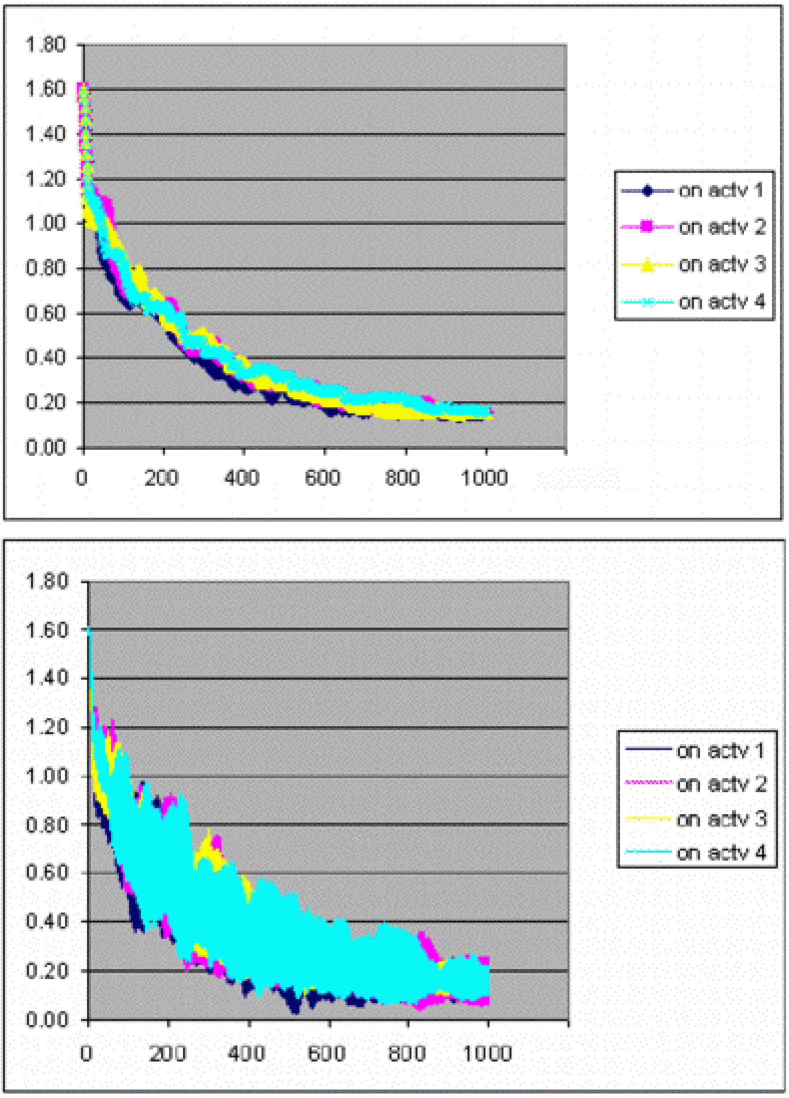


Figure 9. Convergence value D for two different agent positions with two different issue positions (communication on, active issues). Average value graph (left) and standard error graph (right) are shown

6.2

Also, similar results were obtained for situations with passive issues and inter-agent communication. It can be seen from all the graphs that there is no significant difference in the convergence D between runs with different agent and different issue positions. Further, the standard error graphs are similar. Results show that the agents' positions and orientations at the start of the simulation and the issues' positions in the arena do not influence the simulation, i.e. the convergence value D and the standard error were not influenced.

6.3

The results connected with agents and issues initial positions indicate that it is legitimate to look at the specific experimental situations presented in Table 10. Therefore, in the following table, agents' and issues' initial positions are no longer specified.

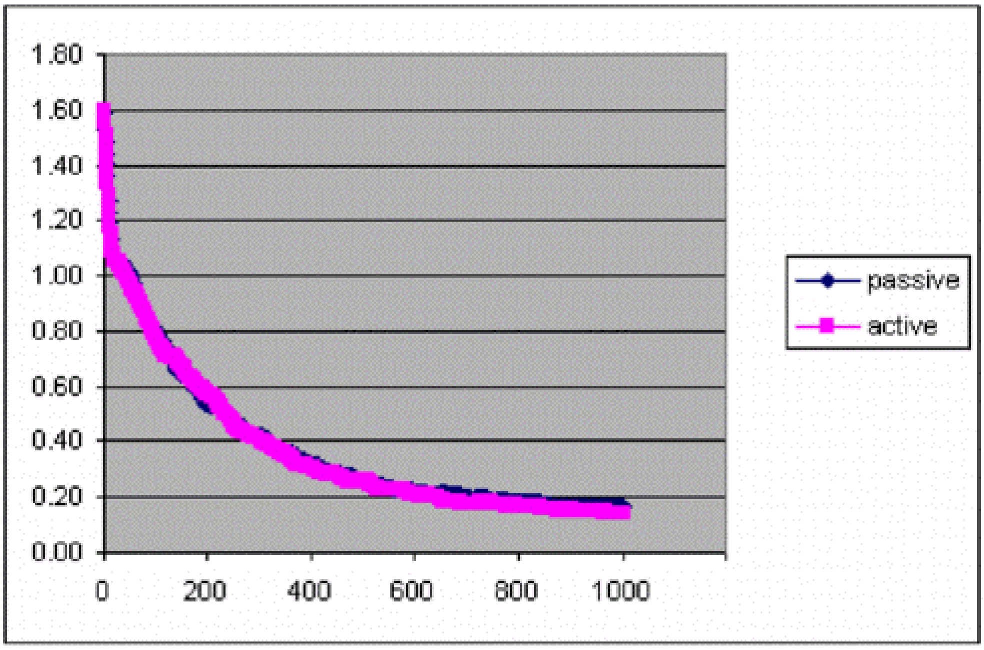
NO	AGENTS	COMM OFF		COMM ON	
		issues pass	issues active	issues pass	issues active
3	random	3p	3a	3cp	3ca
4	3n/3a/3f	4p	4a	4cp	4ca
5	8n 1a	5p	5a	5cp	5ca
6	8a 1n	6p	6a	6cp	6ca
7	4n 4f 1a	7p	7a	7cp	7ca

Table 10. All different experimental situations studied here. For every different experimental situation (cell entry in the table), 20 independent simulations were run

The influence of issues dynamics on the simulation

6.4

The sum of the results for all experimental situations with passive issues and all with active issues is presented below (Figure 10).



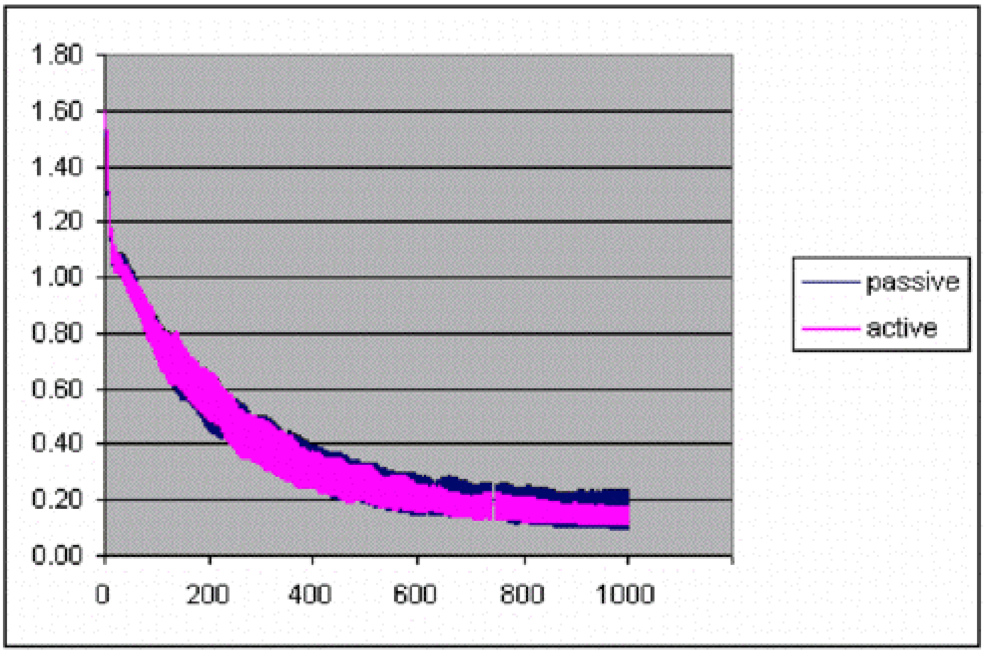


Figure 10. Comparison of all situations with passive issues and active issues. Top: average convergence D graph, bottom: standard error of D graph

6.5

It is clear from Figure 10 that very similar results were obtained from situations involving active issues and passive issues: there is no significant difference in the results with respect to the convergence value D. The only visible difference in the results concerns the standard error value, which is bigger for the passive situation. It implies that the situations involving active issues show more stability than those in which the issues are passive.

The influence of inter-agent communications on the simulation

6.6

A summary of the results for all experimental situations without inter-agent communication and with inter-agent communication is presented below (Figure 11).

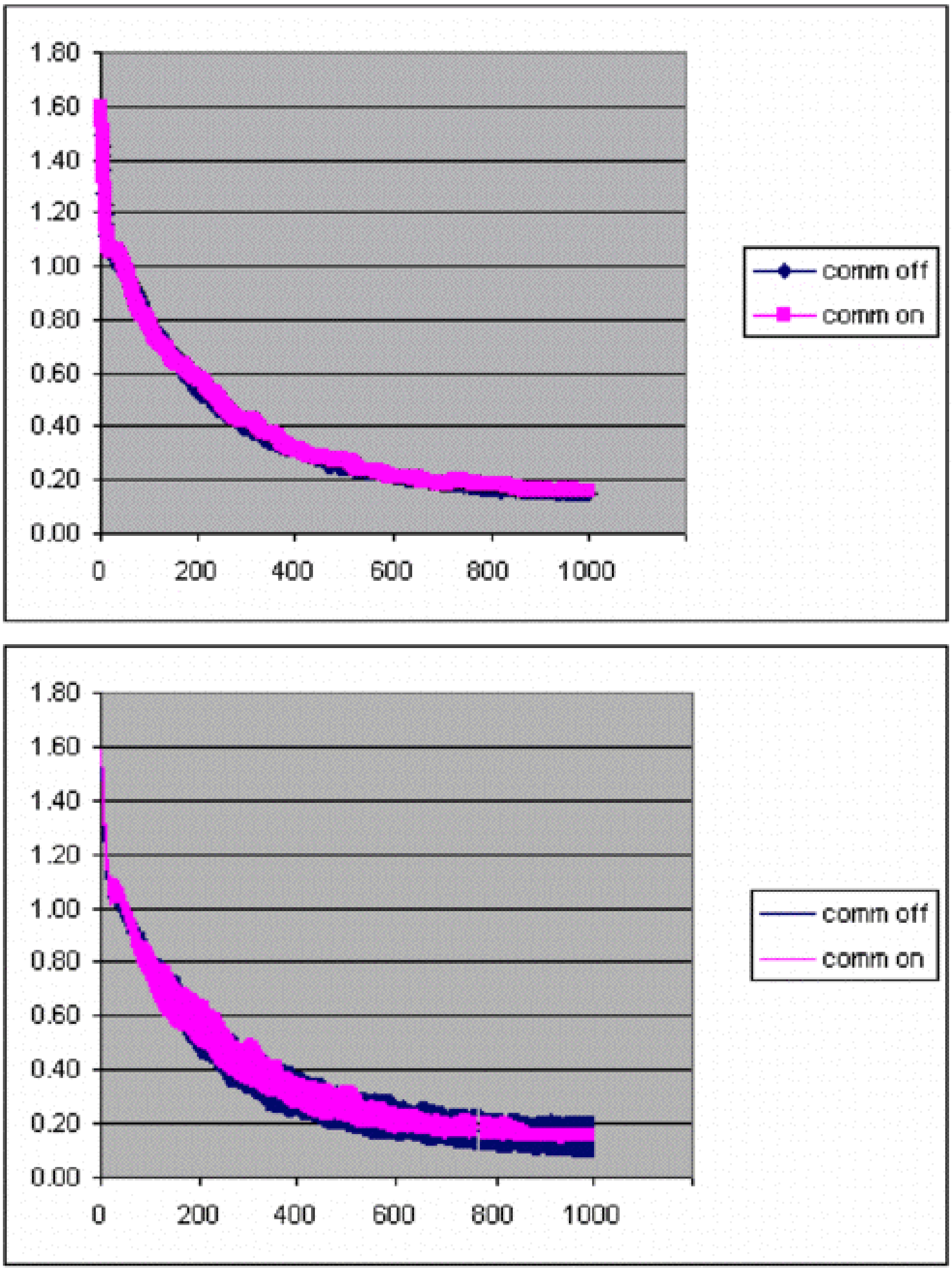


Figure 11. Comparison of all situations with inter-agent communication off and on. Top: average convergence D graph, bottom: standard error of D graph

6.7

Results from Figure 11 show very similar results for both situations (communication off and communication on). There is no significant difference in the results connected with convergence D. Some visible difference in the standard error value (which is bigger for the situations without communication) can be seen. It implies that the situation with inter-agent communication exhibits more stability than situations without inter-agent communication.

The influence of initial agent types on the simulation

6.8

Results concerning the influence of issue activity (6.2) and agent communication (6.3) suggest that it is legitimate to compare the overall data for experimental situations with different initial agent types (rows number 3-7 in Table 10). The sum of all results is presented below (Figure 12).

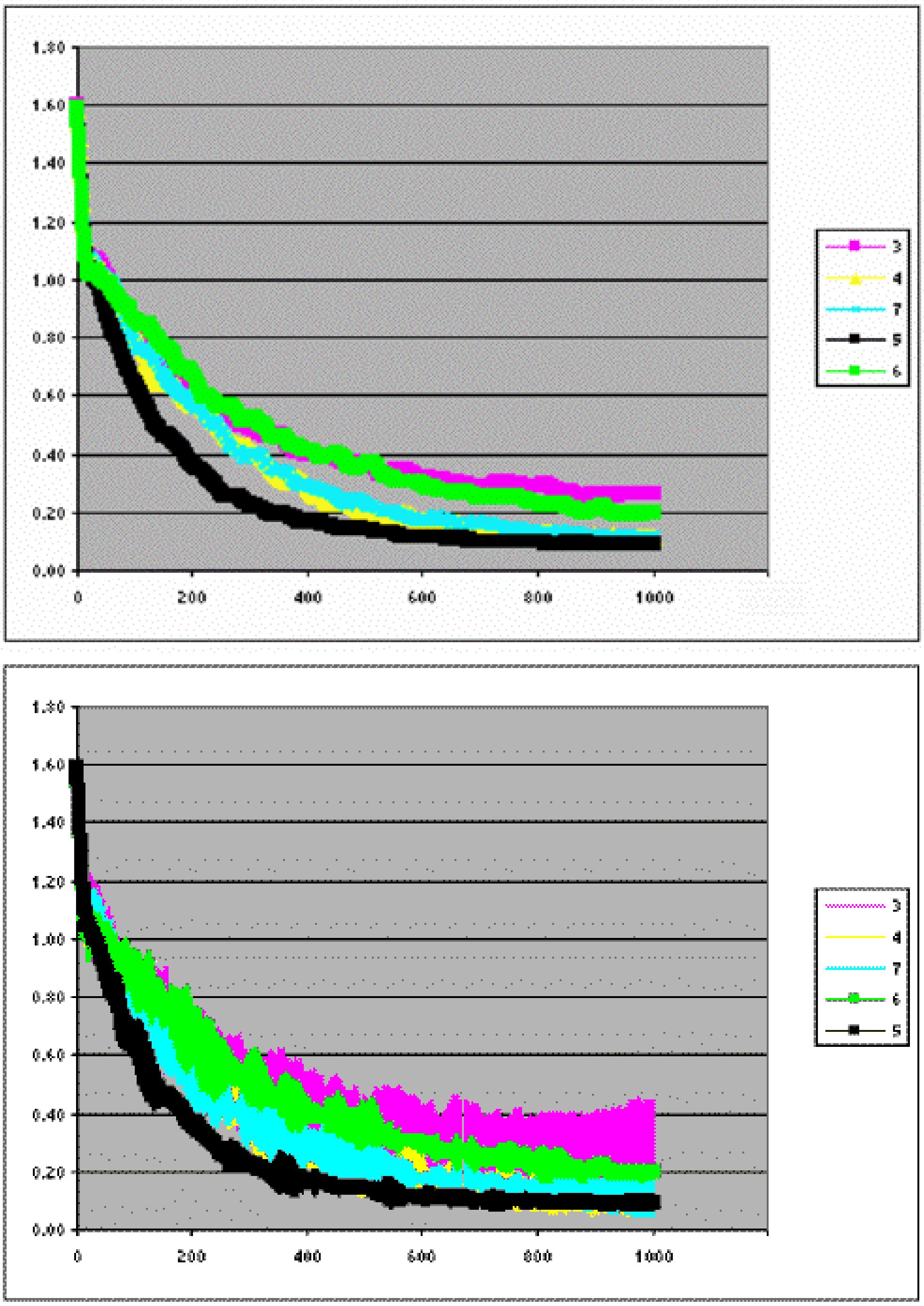


Figure 12. Comparison of all experimental situations with different initial agents' types. Top: average convergence D graph, bottom: standard error of D graph

6.9

The results from Figure 12 indicate that the situation with all random agents (number 3) shows the biggest average convergence value D and standard errors, compared to all other situations. This is probably due to the fact that this scenario contains the highest number of agents with indeterminate socio-political type (agents without distinct attitudes toward issues in the arena) at the start of the simulation. They are always somewhere around issues, although never very close. It is especially evident in the simulations without inter-agent communication and without issue dynamics, when they are not influenced by other agents and not even by issues.

6.10

Similar overall results were obtained for the situation with three neo-liberal, alternative and fundamentalist agents (number 4 in Table 10), and for the situation with four neo-liberal, four fundamentalist and one alternative agent (number 7). Here, the average and standard errors of convergence values D are very similar. The agents converge very smoothly toward issues without significant fluctuations of D. These two situations (number 4 and 7) showed, at the end of the simulations, average D values that are in between those of the overall result graph.

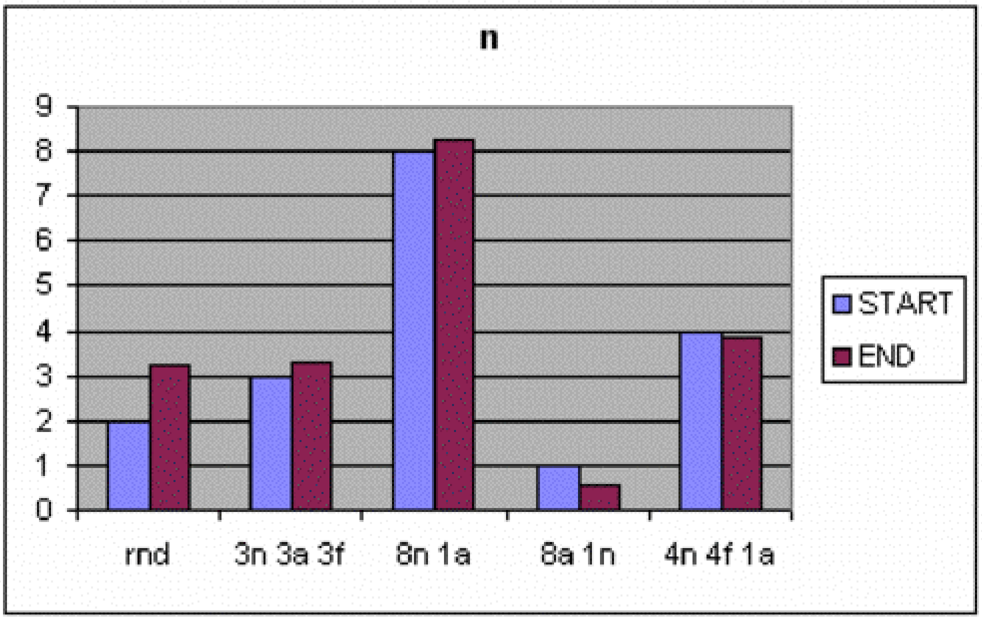
6.11

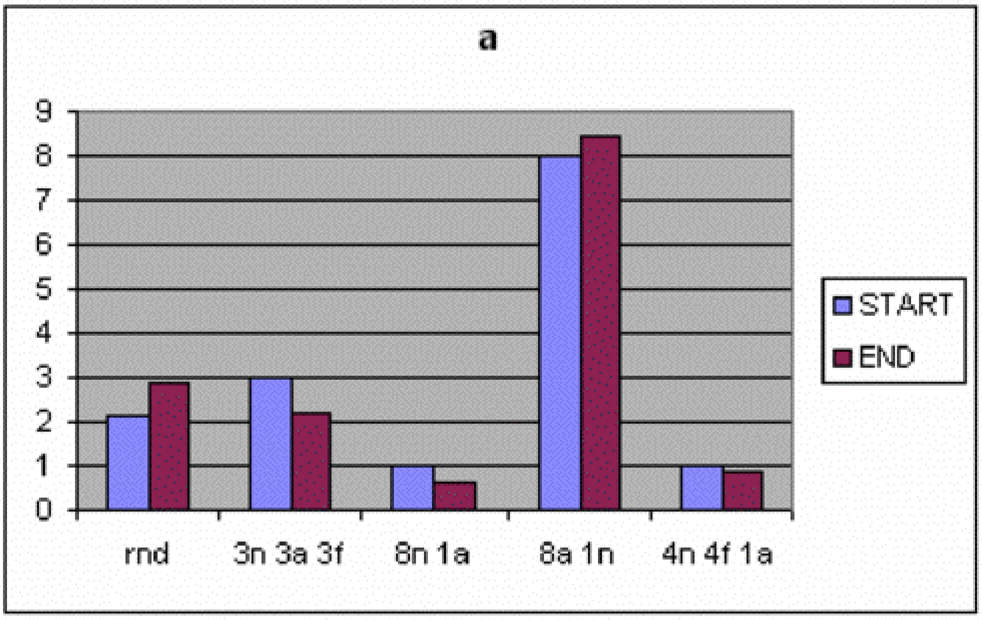
The situation with eight alternative and one neo-liberal agent (number 6 in Table 10) shows high average standard errors of D. In contrast, the situation with eight neo-liberal and one alternative agent (number 5) shows the smallest average and standard error of D during the whole simulation. It also has the fastest convergence to a stable value for all of the situations. This data implies that neo-liberal agents seem to be more 'decisive' than alternative agents. From Table 2 we see that neo-liberal agents have 4 positive, 2 negative and 2 neutral attitudes toward issues, whereas alternative agents have 5 neutral, 2 positive and 1 negative attitudes.

The changes of the initial agent types during the simulation

6.12

The changes of the initial agent types during the simulation were studied by a comparison of agent types in the arena at the start and at the end of each simulation. Moreover, screenshots of the arena at the end of every simulation were taken. Figure 13 summarises all results for experimental situations with different initial agents' types.





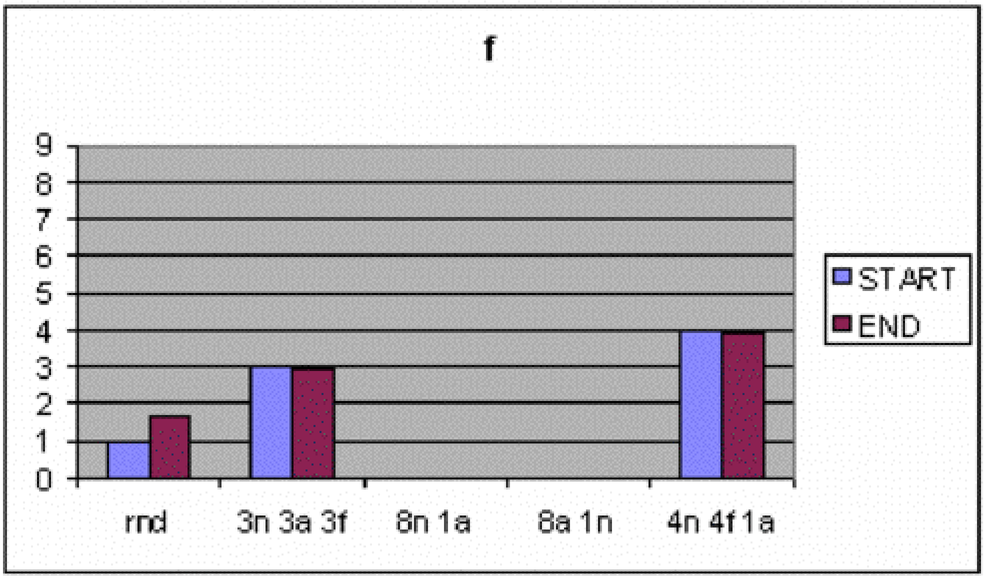


Figure 13. Comparison of average number of neo-liberal (top), alternative (middle) and fundamentalist (bottom) agents at the start and at the end of the simulation for experimental situations with different initial agent types

6.13

From the results in Figure 13 it can be seen that in most cases the number of agents with neo-liberal, alternative and fundamentalist socio-political types at the end of simulation is similar to the number at the start.[8]

6.14

In the situation with one alternative agent among eight neo-liberal agents (number 5 in Table 10), and the situation with one neo-liberal agent among eight alternative agents (number 6), we find similar results, in that agents that were originally outnumbered changed the other agents. In one run, a single neo-liberal agent changed the types of all other alternative agents in the arena. Moreover, in a run with one alternative agent among four neo-liberal and fundamentalist (number 7), a single alternative agent changed the types of all other agents. Overall results statistically show that all 'single agents' (only one agent of this type at the start of simulation) in most of the cases remained unchanged during the simulations.

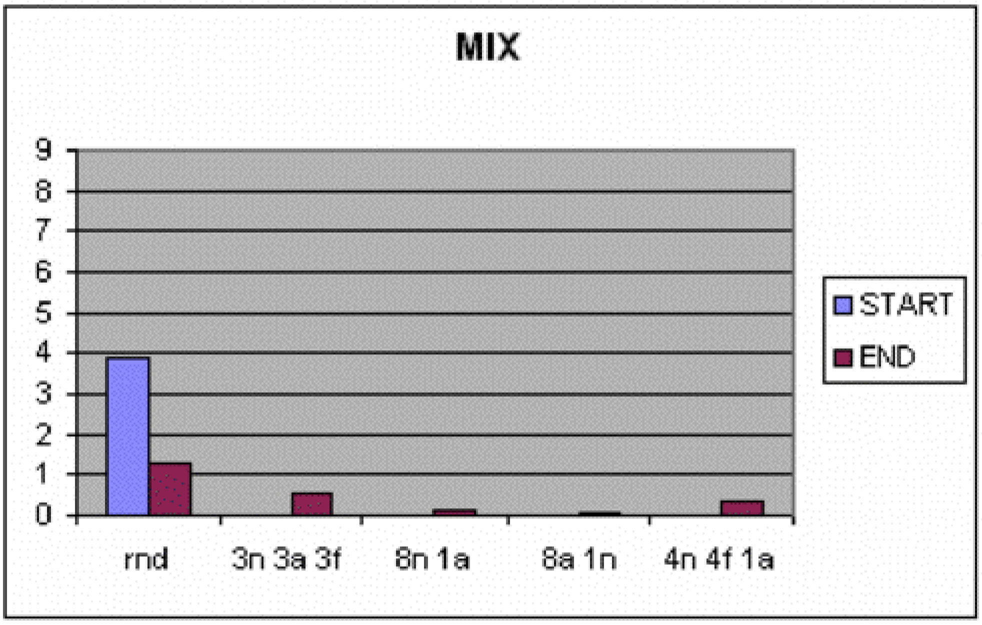


Figure 14. Comparison of average number of agents with indeterminate socio-political types at the start and at the end of simulation for experimental situations with different initial agent types

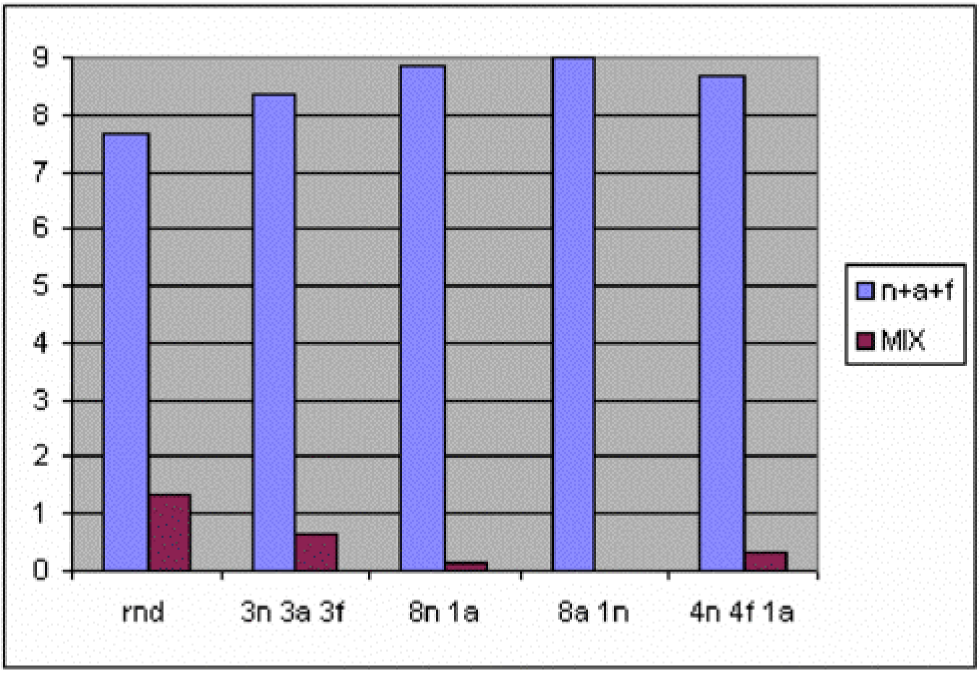


Figure 15. Comparison of average number of agents with determinate (neo-liberal, alternative and fundamentalist) and indeterminate socio-political types at the end of simulation for experimental situations with different initial agent types

6.15

Figure 15 shows that the number of agents with indeterminate types at the end of simulations is always very small (one or none). Even in the random situation, when there are more agents with indeterminate type at the start, there are significantly fewer at the end (Figure 14). Those agents showed 'weakness' during the simulation, i.e.

they changed to other types. It shows a simulation trend towards agents in the arena with 'determinate' types (neo-liberal, alternative and fundamentalist) which tend to keep their types unchanged during the simulations. This implies that our chosen communication algorithm (Table 5) favours agents with determinate socio-political types.

6.16

When compared to passive issues with communication off, all situations which made use of both active issues and inter-agent communication demonstrated a clustering of agents at the end of the simulation. Clustering seems to be more intensive in some situations, but it is hard to define at this point since clustering was not studied systematically across all runs. Further research into the significance clustering is therefore indicated.

Agents' contacts

6.17

Further research is necessary to interpret the data on the number of inter-agent contacts during the simulation, since it seems that this data is compromised because of a high standard error value. It appears that there is a higher number of agents' contacts in situations with inter-agent communication. It also appears that there is no significant difference between situations with passive or active issues. Again, further investigation may yield some detailed conclusions.

Conclusion

7.1

In this paper a multiagent simulation environment for studying agents' socio-political attitudes was presented. It departs from previous work on socio-political attitudes proposed in a high-level theoretical and conceptual model by Petric et al. (2002). Instead of using ideal type characteristics, in our simulations each agent's socio-political type is defined by three components: neo-liberal, alternative and fundamentalist. Our simulation model followed a bottom-up philosophy where the model is grounded in sensory-motor behaviour of spatially distributed autonomous agents, using the Webots simulation software. The focus of our research was the dynamics of agents' attitude changes.

7.2

As presented here, 400 simulation runs were performed. Experimental results show that initial physical positions and orientation of the agents and position of the issues did not influence the simulation outcome. Likewise, the issues' dynamics and inter-agent communication did not have significant impact on the simulation outcome. However, situations with active issues and inter-agent communication showed more stability during simulation. This is due to the fact that active issues (issues with a high level of importance) attract higher number of agents, which then leads to more communications between agents (agents that gather around issues).

7.3

Simulation runs with different initial agents' types show that agents with indeterminate socio-political types have difficulty in 'surviving' (as an agent type) in the simulation. In most cases, they change to neo-liberal, alternative or fundamentalist agents. It seems that the chosen communication algorithm favours agents with determinate socio-political types. In future work, based on existing research in communication and signalling theory, different communication algorithms and their influence on agent types should be investigated.[9]

7.4

The comparison between situations with different starting agent types shows that situations with more neo-liberal agents exhibit the smoothest convergence. In contrast, situations with mostly alternative agents show the worst convergence[10]. It can be directly explained by the model (Table 2), where alternative agents have mostly neutral attitudes and therefore proved indecisive in our simulations.

7.5

On the other hand, neo-liberal, alternative and fundamentalist agents showed equal strength in the simulation and were consistent in most cases. This is in accordance with Petric et al. (2002) where, with regard to social attitudes, the authors claimed: "Since these accounts of our political beliefs are essentially products of what originally used to be philosophical discourse, they are highly consistent and therefore stimulating in the context of agent modelling".

7.6

In future work a further investigation of the parameters used in the present study could provide supportive arguments and explanations for some of our results. For example, the counter-intuitive result that agent communication did not have any significant impact on the simulation outcome might turn out to be due to specific parameters used in the simulation. Thus, a different design of the agents, the environment, or the communication algorithms might lead to different outcomes that could highlight under what conditions communication could be beneficial.

7.7

Also, future work could rework and further develop our underlying model of socio-political attitudes. The work presented in this paper provides a first step towards a test bed for research in socio-political attitudes. One line of research that we are interested in pursuing is the separation of emotion engines from social attitude engines in autonomous agents (as was suggested in Petric et al. (2002)). In future work, the social attitude engine could be extended by an emotional engine in order to study relationships and differences between these two engines. For this purpose, agents' attitudes toward one another as well toward issues have to be modelled. This feature is the sine qua non in the study of more complex social behaviour, particularly in accounting for the embodied and situated nature of human behaviour.

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Notes

[1] For advanced reading about Lyotard's theory of 'metanarratives', James' interpretation and possible application in the multiagent systems please refer to Lyotard (1979; 1984), Jameson (1984) and Petric (2001)

[2] For examples of Webots simulations please refer to the Webots web site at www.cyberbotics.com.

[3] The Khepera robot is widely used in AI research community. It is small, practical and designed for research and education. The Webots simulation package is equipped with full support for Khepera robots. For more details, please refer to the Khepera web site at www.k-team.com.

[4] During test simulation runs issues' and agents' emitter ranges were adjusted in order to obtain suitable physical proximity when an agent perceived an issue or another agent (i.e. when the agent's receiver receives an issue's or another agent's signal). Larger ranges result in agents that are communicating although they are physically remote, smaller ranges make the reception of signals unlikely.

[5] Test runs have shown that the activation of three issue sensors occurs when two, three or four agents are present around the issue. The exact number depends on the agents' positions in relation to the issue's sensors, but in most cases it represents the presence of three agents.

[6] When a scenario contains ten or more agents, the Webots simulation software runs very slowly.

[7] During simulation all agents show a tendency to gather around issues towards which they have positive attitudes. In this way aggregations of agents positioned around issues are formed.

[8] Standard error values for all data were also calculated.

[9] For some references about communication theory models please refer to Hauser (1997), Smith (1977) and Pettersson (1993).

[10] Except in the case of the random situation that contained the highest number of agents with indeterminate socio-political type, which shows the worst overall convergence toward issues.

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